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Applying Hyper-Fuzzy Extended Kalman Filter to Indoor Security Monitoring

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Abstract
This paper presents a new monitoring security system, based on data fusion (DF) from three heterogeneous of sensors which are pressure (PR), active sonar (AS) and infrared (IR). Sensors similarity and complementarity concepts are applied after proper data in real-time. Data is then fed to a Fuzzified Extended Kalman Filter (FEKF) which perform the data fusion. Based on the risk/suspiciousness degree of the monitoring system, moving agents are assessed. A Hyper-Fuzzy logic is utilized in the system as a decision making sub-system that allows the monitored area to be carefully and completely checked for any abnormal activities. The system is then animated to show how the fusion and visualize monitoring.

Keywords: *Multi-Sensor Data Fusion, Feature Extraction, Fuzzified Extended Kalman Filter, Hyper-Fuzzy, Similarity and Complementarity, Measurements Fusion, State Vector Fusion.*

Nomenclature

DF	Data Fusion
PR	Pressure Sensor
AS	Active Sonar
IR	Infrared Sensor
KF	Kalman Filter
EKF	Extended Kalman Filter
FEKF	Fuzzified EKF
AD	Arrival Direction
AT	Arrival Time
MF	Measurement Fusion
SVF	State Vector Fusion
FL I	Fuzzy Logic I
FL II	Fuzzy Logic II
HF	Hyper-Fuzzy
MaN	Number of Moving Agents
AsV	Value of the Assets
AdS	Distance from Assets
SD	Suspiciousness Degree

1. Introduction
In the past years, the increase of buildings and homes breaches grabbed the attention of governments and researchers to develop more reliable security monitoring systems that can detect the behaviors of intruders and take action. Multi-Sensor fusion plays an important role in modern security systems which can provide more robust and capable data processing that wouldn't be possible with the use of systems that are built based on a single sensor data. [1]

The principle of multisensor measurements fusion has also been used in military applications for a long time to achieve precise target tracking and recognition. Similar techniques and models are used in medical applications and robotics to enhance the quality of their monitoring and guidance. Multiple types of sensors are usually combined to improve estimations based on appropriate algorithms that can maximize their accuracy. [6,7]

Designing such systems requires proper selection of homogeneous sensors types and processing techniques since the fused provided data can lead to unreliable estimations and consequently poorer decisions by the system which is not acceptable in most cases. Another advantage of fusing different sources of data is the capability of blending accurate and inaccurate measurements that are delivered from sensors with unequal variances and have unknown biases [6].

Similarity and complementarity principles are applied in this paper to pre-process the raw sensors information before they are fused to prevent the system from making imprecise conclusions. The two processes will help to pass the only consistent data and reject the untrustworthy sensors measurements that contain undesirable noisy data which will help the monitoring system to make reasonable judgements of the environment under surveillance [3].

The extracted features from sonar and infrared are combined to serve as one virtual data that represents the position and velocity of any moving object. The pressure sensors floor array will assist the monitoring system to locate the moving agents providing their weights and location. The weights are important to recognize each person with his/her distinctive weight where it's assumed that no person share the same body weight with others. Raw data from sensors are not complete and may not reflect the real environment being observed since each sensor shows part of the truth. Fusing all these sensors data together will result in more reliable observation system that shows the bigger picture with proper details, which can then be utilized to understand the different behaviors of the agents under supervision.

In section 2, a survey of related work is given. Section 3 provides the system's sensors functionality and their roles in monitoring the area under observation. In sections 4-7, methods of sensors selection, preprocessing, and fusing are provided. Section 8 discusses the EKF and how it is Fuzzified applying Fuzzy Logic. Section 9 shows the system dynamic model; while, section 10 examine the Hyper-Fuzzy decision method. In section 11, the system animation is explained. And finally, section 12 an investigation and discussion of the monitoring system results are presented.

2. Related Work

Many papers and researches have been accomplished on multisensor data fusion applying several methods and approaches. This paper is not the first of its kind; however, the type of sensors, sensors selection, filtering, and decision making present an altered combination methodology as a new way of tackling the same goals in addition to the classification of the target being tracked and monitored. For example, in [3] the laser and radio frequency were the major sensors fused to achieve a similar goal as this paper intend to do. In addition, the filtering process was based on EKF alone without the aid of Fuzzy Logic as a technique of improving the estimation. Another work was done employing image and acoustic radar sensors [6] as the two sensorial modules that were fused to detect the intruders in the covered zone. Neural network algorithm was applied to detect the moving agents and fire an alarm in case the active breaching.
The most recent challenges and development of data sensor fusion are addressed in [18] where they discussed the limitations of the multi-sensor fusion applications and their advantages. Some advances were in algorithms classification and fusion methods such as wavelet-based and neural network fusion. In remote sensory data fusion, their work explains the identification, classification, and detection methods of objects applied to fusion of images. The suggested methods in [18] may improve the capability of image sensor fusion by enhancing the fusion algorithms and refining the quality of assessment performance.
Sensor Fusion as an application has found its way in navigation system utilizing GPS, inertial sensors, and vision sensors that are currently hot topics in automation industry. The orientation of the vehicles and robots as well as the position estimation in real-time has enhanced with more heterogenous sensors data that being fused to achieve those goals as was investigated in [19,20].

3. The Sensors

This anticipated system model harness the advantages of three types of sensor arrays to realize the environment under surveillance by tracking and detecting the quantity of agents and their locations with respect to the assets positions. First, the pressure sensor array will provide the number of moving and stationary objects associated with their different weights and pressure on the monitored floor. Then, a group of AS and IR sensors will start tracking each agent position and velocity.

A. Sonar Sensor

Sonar acronym is derived from SOund Navigation And Ranging by Frederick Vinton Hunt in 1942 which refers to both passive and active acoustic range finding devices. [12] Passive sonars measures direction and distance of the noise that is made by the tracked creature or machine without transmitting any signal. Alternatively, in active sonar (AS) a sound pulse is emitted by the transmitter and then received after a period of time "delay" by the receiver. The receiver in AS obtain the arrival time (AT) and the arrival direction (AD) for every pulse transmitted by measuring the time difference between both transmitted and received pulse [11,13]. Figure 1 explains the AS components and principle.

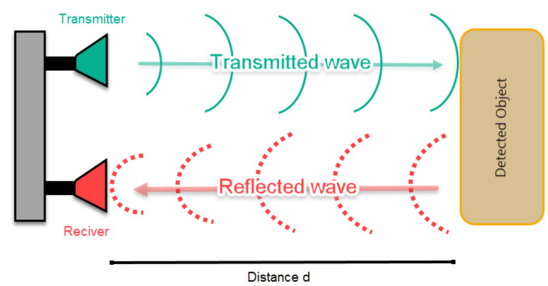

Figure 1: Active Sonar Components and Principle

Equation (1) shows the how the distance of a tracked object is calculated by multiplying the time difference between the outgoing and incoming echo and the speed of light divided by 2 [5,11,13]:

$$d_k = \frac{c*\Delta t_k}{2} \tag{1}$$

AS distance measurement is affected by the temperature and pressure of air, and the chemical structure of air components; however, AS are not tolerated by the other distractions like smoke, light brightness, and electromagnetic fields interventions. [5,12]

B. Infrared Sensor (IR)

Infrared refers to the ability to emit the electromagnetic radiation toward a target to detect the temperature and the motion. The emitted radiation from IR sensors is invisible to the human's eye but it can be received by a photodiode that is sensitive to the infrared light and have the same wavelength of the emitter diode. IR is famous for real time tracking applications like the proposed security system.
Although IR sensors are reliable for close range distance measurements, they also provide a good approximation of the long range object detection. [5]
IR sensor fit the purpose of this proposed security monitoring system since it is capable of detecting any living creature and any lifeless object. IR photodiode senses the emitted infrared light from far distances in wide areas. There are many types of IRs based on their output such as voltage or digital output. Infrared sensor detection accuracy can be distracted by the temperature of the room and the temperature of the tracked objects/agents. [6,14]

C. Pressure Sensors Floor Array

One of the highly effective sensors that is barely used in security systems is the pressure sensor. Floor integrated pressure sensitive system is utilized in this proposed security monitoring model to obtain the weight and location of any moving or stationary objects/people. The monitored area is completely covered with pressure tiles to fulfil this purpose. Every stationary object is marked in the system with its respective weight and location; so that the monitoring system is able to recognize whether the valuable assets has been moved or stolen and to distinguish between what or who needs to be monitored. Once an agent or a guard step on any part of the floor, the system will start measuring and tracking his/her steps pressure and altitude on the monitored surface [7]. The monitored area is assumed to be all covered with pressure sensors tiles as the dotted lines in Figure 2.

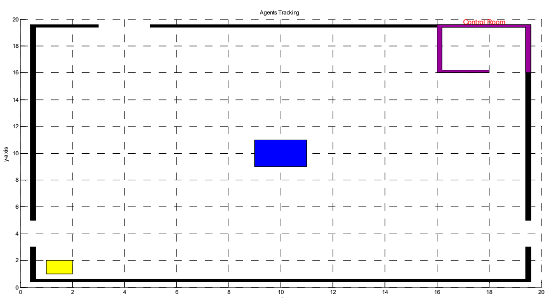

Figure 2: Pressure floor array as animated in the proposed system "Matlab"

4. Preprocessing and Sensors Selection

Since there are three types of sensors (Sonar, IR, and Pressure) in the monitoring model; three Sonars and three IRs are assigned for each agent in the monitored area. The raw data collected from each sensor within the same group need to be fused before the fusion of the three categories to obtain one measurements stream from each type. This preprocessing will the help the system to blend more reliable data. Measurements Fusion (MF) is applied to blend all the sonars data together and the IRs together to end up with only one data stream for each category. For the pressure sensors, it is consisted of floor array and it's impossible to stack more than one tile on each other to have multiple tiles measurements.

5. Sensors Complementary

In this multi-data fusion system, sensors need to communicate and collaborate dynamically to deliver a clear full picture of the environment under surveillance. All individual uncertain geometric sensory data have to alternate their vision of the agents with each other in a way that it tells the system the current situation, where sometimes one sensor has a missing or misleading measurements that lead to unreliable decision making. [3,10]

6. Similar Sensors Fusion "Sensors Similarity"

The replicated Sonars and IR's sensors data are combined into one sensory data; where each sensor has a different view of the environment under surveillance and its components. While other sensor similarity techniques sacrifice some sensory data in order to select the similar/close range data as in [3, 5]; fusing the sensors by applying Measurement Fusion method can harvest the advantages of all sensors in the monitored environment.

Measurements Fusion (MF) is the first prominent method of blending sensors that have similar properties and functionality. Unlike State Vector Fusion (SVF), MF can blend the data prior to the estimation process. [9,15]. Measurements vectors Z_k^1 , Z_k^2 *and* Z_k^3 from the three Sonars and their associated measurements' noises "R_s^1, R_s^2 *and* R_s^3" are combined into a single new vector Z_s^4 recursively.

For two sensors measurements (Z_k^1 and Z_k^2) and their errors (R_s^1 *and* R_s^2) we may find the resulting combined measurement vector applying MF as following:

$$Z_k^{1,2} = Z_k^1 - (R_s^1 * (R_s^1 + R_s^2)^{-1} * (Z_k^2 - Z_k^1)) \tag{2}$$

$$R_k^{1,2} = ((R_k^1)^{-1} + (R_k^2)^{-1})^{-1} \tag{3}$$

However, for three sensors measurements $Z_k^{1,2,3}$ is formulated by replacing $Z_k^1$with Z_k^3 and substituting $Z_k^{1,2}$ into Z_k^2 . Then the three sensors measurements Z_k^1 , Z_k^2 *and* Z_k^3, as in this proposed monitoring system, the MF equations are computed as:

$$Z_k^{1,2,3} = [(R_s^1 * R_s^2 * Z_k^3 + R_s^1 * R_s^3 * Z_k^2 + R_s^2 * R_s^3 * Z_k^1) * [R_s^1 * R_s^2 + R_s^1 * R_s^3 + R_s^2 * R_s^3]^{-1}] \tag{4}$$

And for the measurements errors covariances become:

$$\mathrm{R}_k^{1,2,3} = ((\mathrm{R}_k^1)^{-1} + (\mathrm{R}_k^2)^{-1} + (\mathrm{R}_k^3)^{-1})^{-1} \tag{5}$$

After applying MF to three homogenous sonar sensors we get the fused MF as in Figure 3.

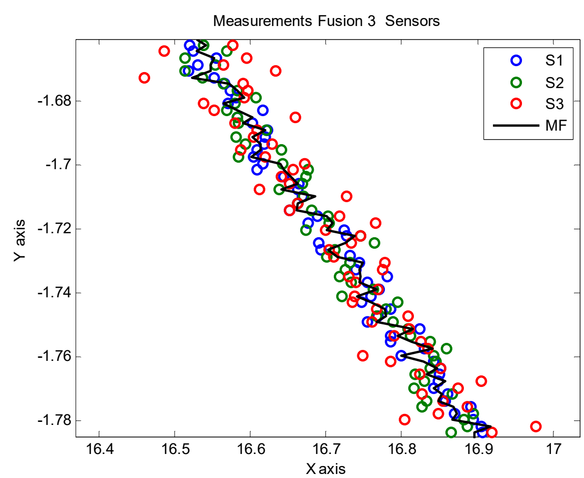

Figure 3: MF of three sonar sensors

The resultant fused measurements and their noise covariances are then filtered through separate Kalman Filters where the State Vector Fusion (SVF) will be applied later.

7. Sensor Fusion Applying State Vector Fusion Method

Unifying the sensory data of the same type of sensors in the preprocessing phase applying MF is the first fusing stage; however, the resulting combined data from the three types of sensors are then fused altogether utilizing the State Vector Fusion (SVF) technique. For two sensors to be fused by SVF, the MF fused measurements for the same type of sensors is fused with the second type of sensor as following [5,15]. Pressure sensor state vector ($\hat{x}_{k-1}^{prs}$) is fused with IR sensor state vector ($\hat{x}_{k-1}^{IR}$) first equation (6) and then the AS sensor state vector ($\hat{x}_{k-1}^{AS}$) is fused with the resulting first vector equation (8) where the new estimate is given by the following equation:

$$\hat{x}_{k-1}^{1} = \hat{x}_{k-1}^{Prs} + P_{k-1}^{prs}[\mathrm{P}_{k-1}^{prs} + P_{k-1}^{IR}]^{-1}[\hat{x}_{k-1}^{IR} - \hat{x}_{k-1}^{Prs}] \quad (6)$$

Whereas, P_{k-1}^{prs} and P_{k-1}^{IR} are the error covariance matrices of both pressure and IR sensors respectively. Their combined covariances can now be stated as in equation (7):

$$P_{k-1}^{1} = P_{k-1}^{prs} + P_{k-1}^{prs}[P_{k-1}^{prs} + P_{k-1}^{IR}]^{-1}\, P_{k-1}^{prs\,T} \quad (7)$$

The AS fusion with both previous combined sensors is computed by equations (8,9) as:

$$\hat{x}_{k-1}^{2} = \hat{x}_{k-1}^{AS} + P_{k-1}^{AS}[P_{k-1}^{AS} + P_{k-1}^{1}]^{-1}[\hat{x}_{k-1}^{1} - \hat{x}_{k-1}^{AS}] \quad (8)$$

$$P_{k-1}^{2} = P_{k-1}^{AS} + P_{k-1}^{AS}[P_{k-1}^{AS} + P_{k-1}^{1}]^{-1}\, {P_{k-1}^{AS}}^{T} \quad (9)$$

Where the results of all sensory data SVF are then fed into FEKF algorithm to enhance the estimation and tracking accuracy of the monitoring system which will lead to reliable decision that can reach beyond the results of other proposed fusion methodologies.

8. Fuzzified Extended Kalman Filter

Kalman Filter (KF) is a widely-used estimation algorithm in many modern systems which could be found in many engineering applications. In this paper, the nonlinear extension of KF is applied to estimate the states of any moving object based on the data provided from the pressure, sonar, and infrared sensors that are implemented in the monitoring/tracking model. All sensors' data are fused using EKF which allow to increase the accuracy of the system estimation beyond the abilities of KF and EKF alone. All model imperfect components may add unwanted additions to the measurements which are denoted as the measurement and system errors. These errors are characterized as Gaussian white noise [3,8,16].
Extended Kalman Filter similar the Kalman Filter, consists of two iterative stages which are the prediction/projection and update/estimation for the current time instances with no need of storing or processing all the previous predicted measurements; instead, it only requires the latest measurements to estimate the current estimate [19].
Consider the following stochastic model of a nonlinear discrete difference equations as following:

$$\tilde{x}_k = f(\hat{x}_{k-1}, u_{k-1}) + w_{k-1} \quad (10)$$
$$\tilde{\mathrm{y}}_{\mathrm{k}} = \mathrm{h}(\tilde{\mathrm{x}}_{\mathrm{k-1}}) + \mathrm{v}_{\mathrm{k-1}} \quad (11)$$

In Equation (10), the $x \in \Re^n$ is a state vector, f is a nonlinear function that links the prior time step $k-1$ to k which is the current time step, and w_{k-1} is a white Gaussian with zero mean system noise. While in equation (11), $y \in \Re^r$ is the measurement equation, h is a nonlinear function that links the measurement vector y to the state vector x, and v_{k-1} is a white Gaussian with zero mean measurement noise [17].

A. Prediction Stage

The filter first forecast the current state based on the a posteriori estimation of $\hat{x}$ as in equation (12).

$$\tilde{x}_k = f(\hat{x}_{k-1}) \quad (12)$$

Once the state is predicted, the error covariance P is calculated as in (13):

$$P_k = F_{k-1}P_{k-1}F_{k-1}^T + Q_{k-1} \quad (13)$$

Where F is the Jacobian of $f(.)$ with respect to x is obtained (equations (14,15)) to determine the error covariance which can be computed by taking the partial derivatives of the nonlinear state vector elements to linearize about the mean and the variance of the existing measurements at each time step.

$$F_k = \nabla f_k\, |\hat{x}_k \quad (14)$$

$$\nabla f_k = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \cdots & \frac{\partial f_b}{\partial x_n} \end{bmatrix} \quad (15)$$

B. Correction Stage

The predicted/estimated states need to be corrected now by calculating additional set of equations that include the Kalman gain K, updated state vector $\hat{x}_k$ and error covariance P_k as following:

$$K_k = P_k H_k^T (H_k P_k H_k^T + R_k)^{-1} \quad (16)$$

Where H is the Jacobian matrix of h(.) with respect to X as in (17,18):

$$H_k = \nabla h_k\, |\hat{x}_k \quad (17)$$

$$\nabla h_k = \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \cdots & \frac{\partial h_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial h_n}{\partial x_1} & \cdots & \frac{\partial h_b}{\partial x_n} \end{bmatrix} \quad (18)$$

The current state estimation is then calculated by adding the multiplication of Kalman gain and the innovation vector to the a priori state values:

$$\hat{x}_k = \hat{x}_{k-1} + K_k(z_k - h(\hat{x}_{k-1})) \quad (19)$$

Finally, the error covariance matrix can be updated and adjusted to reflect the change of Kalman gain on the next prediction cycle:

$$\mathrm{P}_k = [I - K_k H_k]\mathrm{P}_{k-1} \quad (20)$$

C. EKF Fuzzification

Over the years, fuzzy logic technologies have attracted the attention of various groups of people, including researchers and computer scientists. In particular, it has had a significant role in replacing the commonly used forms of technologies in several engineering and scientific applications, especially signal processing, pattern recognition, not to the mention making of integrated circuits. In addition to this, it is employed in other areas such as approximation reasoning. What is more, fuzzy technology is capable of aiding in making decisions besides creating systems that have a considerable capacity to reason well [3,4]. It should be noted that these particular systems were presented in 1965 by Zadeh. Originally, they were meant to compute and adjust data faced with imprecisions or uncertainties [4]. A salient point to note is that the base of all fuzzy systems is the fuzzy logics and sets, which have been designed to imitate brain functionality for uncertain information.

It has already been established that not all problems involving computing and mathematics are easy to go about. As a matter of fact, many of these problems are complex and may seem impossible to compute. Therefore, mathematical tools such as the fuzzy logic are employed to tackle these types of problems.

The above details showed how the known EKF work with respect to the dynamic system and the sensory data which works well for nonlinear models; however, with the aid of Fuzzy Logic I (FL I), the EKF can perform better and provide a more accurate estimation [16]. The resulting combination of FL I and EKF can be termed as Fuzzified EKF or FEKF.

The measurement noise covariances of the sensors are considered constant in most systems that utilize KFs algorithm for estimation and prediction which may prevent KFs from reaching its optimality [16]. The addition of FL to EKF will reduce the estimation error by making the measurement error covariance R and the system error covariance Q variable instead, which in turn can fine-tune the EKF estimation. FL I has the capability of logical reasoning of inaccurate, indistinct, and insufficient information that lead to more adequate decision making. [4]

FL is a technology that use fuzzy sets, a set with soft boundaries, consisting of universe of discourse (X) which is a class in the set theory. FL needs a membership function $\mu(x)$ that allocate a value between 0 and 1 to every single element in the discourse. $\mu(x)$ will ease the reasoning process of FL [3,4,16]. In general, a fuzzy set can be defined by the following relationship:

$$A = \{x, \mu_A(x) \mid x \in X\} \quad (21)$$

Where A is the fuzzy set of ordered pairs and $\mu_A(x)$ tells to what degree of fuzzy set x belong. For example, if the value of the membership function gets closer to 0, then it is not likely x is a member of the set A; on the other hand, if the value of $\mu_A(x)$ gets closer to 1, the likeliness of x to be a member of A is very likely [4].

In KF, if the process error covariance Q increase, the gain K will increase trust weight of the innovation vector; however, if the measurement error covariance R increase, the gain K will decrease the trust weight of the innovation vector. Both relationships play a huge role in tuning the EKF. To fuzzify EKF, a new variable need to be introduced (α) which is the weight scalar that will increase or decrease the error covariances of both the process and the measurements [16] where these relationships can be expressed as:

$$Q_k = Q\alpha^2 \quad (22)$$

$$R_k = R\alpha^{-2} \quad (23)$$

The weight scalar α is determined by setting a FL I model that relates the polar coordinates Δr and $\Delta\theta$ discrepancies, and the innovation vector $In_k = (z_k - h(\hat{x}_{k-1}))$ to α.

The FL I rules table is shown below (Table 1) which defines the relationship between the change in angles $\Delta\theta$ and the innovation vector In_k by a transitional variable $C_{In/\theta}$. [16]. Figure 4 and Figure 5 explain the FIS system and fuzzy surface of table 1 relationships and how they are selected subsequently.

$C_{In/\theta}$		$\Delta\theta$		
		S	M	L
In_k	S	S	S	M
	M	S	M	L
	L	M	L	L

Table 1: FL I rules associated with transitional variable

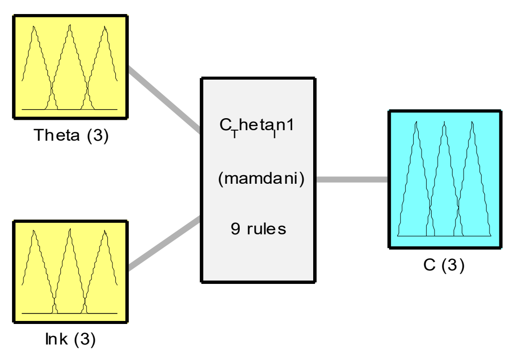

Figure 4: FIS system for transitional variable built by Matlab

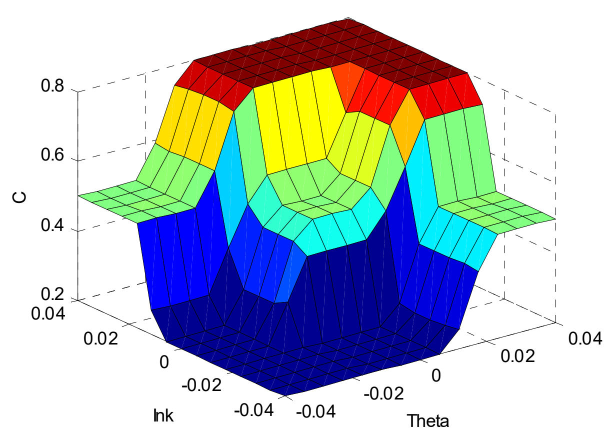

Figure 5: FIS Surface of transitional variable with inputs $\Delta\theta$ and In_k, output $C_{In/\theta}$

This association will then be considered in regard with the distance differences Δr and the weight scalar as shown in Table 2:

α		Δr		
		S	M	L
$C_{In/\theta}$	S	S	M	L
	M	S	S	S
	L	VS	VS	VS

Table 2: FL I rules associated with weight scalar

In the above tables, S stands for small, M stands for medium, L stand for large, and VS stands for very-small value that can be close to zero. Figure 6 and Figure 7 explain the FIS system and fuzzy surface of table 2 relationships and how they are selected subsequently.

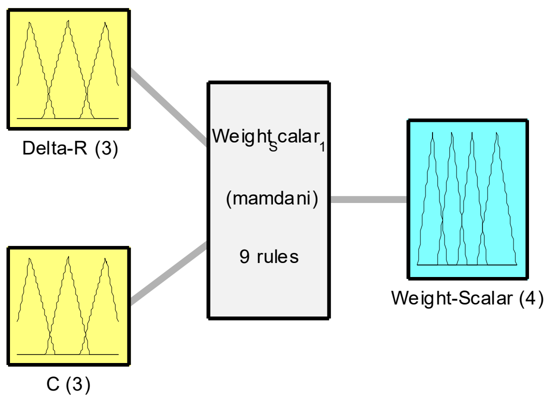

Figure 6: FIS system for transitional variable built by Matlab

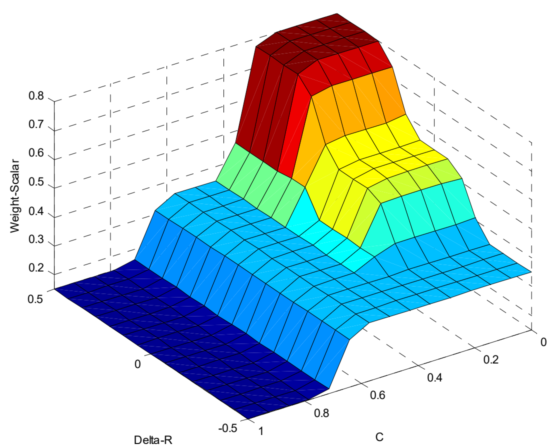

Figure 7: FIS Surface of transitional variable with inputs $\Delta\theta$ and In_k, output $C_{In/\theta}$

The proposed FL I system was added to the EKF which became FEKF that enhanced the filtering and reduced the estimation error of the tracking.

9. Dynamic System Model

System dynamic model that utilize all the heterogeneous sensors estimations and then fuse them is as following:

$$\tilde{x}_k = f(\hat{x}_{k-1}, u_{k-1}) + w_{k-1} \quad (24)$$

$$\begin{bmatrix} \tilde{x}_k(1) \\ \tilde{x}_k(2) \\ \tilde{x}_k(3) \\ \tilde{x}_k(4) \\ \tilde{x}_k(5) \\ \tilde{x}_k(6) \end{bmatrix} = \mathrm{F} * \begin{bmatrix} s_{k-1}^x \\ v_{k-1}^x \\ a_{k-1}^x \\ s_{k-1}^y \\ v_{k-1}^y \\ a_{k-1}^y \end{bmatrix} + \mathrm{B}u_{k-1} + \omega_{k-1} \quad (25)$$

Where s_k is the position, v_k is the velocity and a_k is the acceleration of the tracked agent at the current time estimated from the a priori measurements ($s_{k-1}, v_{k-1}, a_{k-1}$). ω_{k-1} refers to the system noise associated with each measured term. This model equation is applied for both x-axis and y-axis. B is the control vector matrix and u is the control vector that allow the control of the actuators in the system.

The velocity v_{k-1} and acceleration a_{k-1} first get integrated into position value. For the velocity to be calculated, the acceleration gets integrated into velocity value. The state transition matrix, that characterize the Jacobean matrix of nonlinear function (.) , can be written as:

$$F = \begin{bmatrix} 1 & dt & \frac{dt^2}{2} & 0 & 0 & 0 \\ 0 & 1 & dt & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & dt & \frac{dt^2}{2} \\ 0 & 0 & 0 & 0 & 1 & dt \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (26)$$

The process noise matrix is diagonal to all corresponding elements of the nonlinear system dynamic difference equation which result in:

$$Q = \begin{bmatrix} q_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & q_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & q_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & q_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & q_5 & 0 \\ 0 & 0 & 0 & 0 & 0 & q_6 \end{bmatrix} \quad (27)$$

The measurement representation of the model for all states in the system is as follow:

$$\tilde{y}_k = h(\tilde{x}_{k-1}) + v_{k-1} \quad (28)$$

Where:

$$h = \begin{bmatrix} r \\ \theta \end{bmatrix} = \begin{bmatrix} \sqrt{(\tilde{x}_{k-1}(1))^2 + (\tilde{x}_{k-1}(4))^2} \\ atan2(\frac{\tilde{x}_{k-1}(4)}{\tilde{x}_{k-1}(1)}) \end{bmatrix} \quad (29)$$

r and θ are the polar coordinates representation of the distance and the angle between the reference point (sensor location in this case) and the tracked point (agent/object) which will then be transformed into Cartesian coordinates. Hence, the Jacobean matrix of h with respect to x is as following:

$$H=\begin{bmatrix} \frac{\tilde{x}_{k-1}(1)}{\sqrt{\left(\tilde{x}_{k-1}(1)\right)^2+\left(\tilde{x}_{k-1}(4)\right)^2}} & 0 & 0 & \frac{\tilde{x}_{k-1}(4)}{\sqrt{\left(\tilde{x}_{k-1}(1)\right)^2+\left(\tilde{x}_{k-1}(4)\right)^2}} & 0 & 0 \\ \frac{-\tilde{x}_{k-1}(4)}{\left(\tilde{x}_{k-1}(1)\right)^2+\left(\tilde{x}_{k-1}(4)\right)^2} & 0 & 0 & 0 & \frac{\tilde{x}_{k-1}(1)}{\left(\tilde{x}_{k-1}(1)\right)^2+\left(\tilde{x}_{k-1}(4)\right)^2} & 0 \end{bmatrix} \quad (30)$$

r and θ are correlated with different noises (measurement noises) which are not the same for all sensors taking in account the precision of each sensor:

$$R=\begin{bmatrix} r_{var} & 0 \\ 0 & \theta_{var} \end{bmatrix} \quad (31)$$

The proposed model diagram is shown below “Figure 8” which reveals how the data are collected first, then the features of all sensors is extracted and finally the decision making is made by hyper-fuzzy logic.

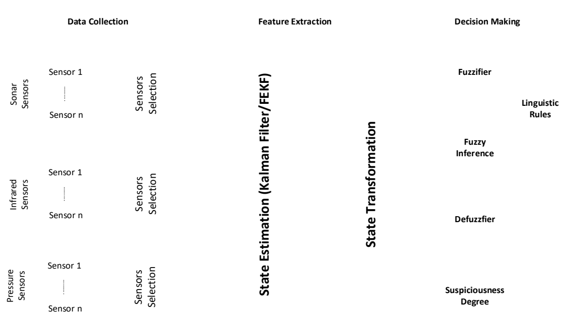

Figure 8: Monitoring System Model Block Diagram

10. Hyper-Fuzzy Decision

FL I only assumed that the systems are deterministic with no uncertainty which doesn’t satisfy its own name “fuzzy” or the vagueness of human reasoning and decision-making that Zadeh substantiated his concepts and theories on. For that, in 1975 he extended FL I with other subgroups that can handle uncertainties in the system in three-dimensional structure. The new system was called Type-2 Fuzzy Logic system or Fuzzy Logic II (FL II) which is more complex and difficult to be implemented if compared with FL I [4].

In 2010, Salim proposed a new extension to the fuzzy set theory that combine the features of both FL I and FL II. The new controller was named Hyper-Fuzzy Logic (HF) which is based on the same membership functions of FL II on the top and the bottom but only apply FL I fuzzy sets [3,4].

Hyper fuzzy has various advantages since it is more advanced than FL I and easy to implement. First of all, it is easily adaptable. Specifically, one can learn how to apply it in various sectors without much problems. Another advantage is its immunity to noise. Another major advantage of HF is that it is considerably flexible. In fact, this system has included functions such as the capability to make human decisions. Furthermore, large quantities of data can be dealt with easily by this system. However, one major setback is that HF has not yet been generalized on its own [4].

HF can be considered a special type of type-2 fuzzy sets. Unlike typical fuzzy, HF provides an allowance for imprecisions. As a matter of fact, it is derived by obtaining concepts of the upper and lower type-2 membership functions and is based on fuzzy sets from type 1 [3,4]. Furthermore, it is applied by utilizing a certain toolbox found in MATLAB software. Figure 11 shows how the HF membership function looks like as a blurred FL I membership function which was extended to contain uncertainty.

To utilize HF logic in this paper, the decisions of the security system are based on the suspiciousness degree (SD) of the moving agents around the monitored assets [4]. The number of moving agents (MaN), their corresponding distances from the assets around the monitored area (AdS), and the value of the asset (AsV) are the three inputs of the HF and the output will be a value between 0 and 12 (Figure 10) that indicates the suspiciousness degree (SD) of each agent at a certain time. The closer the agent to the asset, the more suspicious he/she would become; on the other hand, the farther the agent from the asset the less suspicious he/she is.

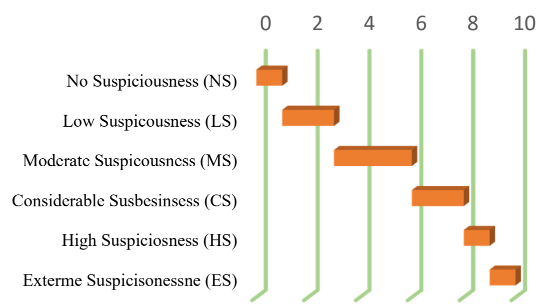

Figure 9: Suspiciousness Degree (SD)

There are six levels of SD, namely, No Suspiciousness (NS), Low Suspiciousness (LS), Moderate Suspiciousness (MS), Considerable Suspiciousness (CS), High Suspiciousness (HS), High Suspiciousness (HS), Extreme Suspiciousness (ES). Figure 9 explains the level of suspiciousness and their matching values.

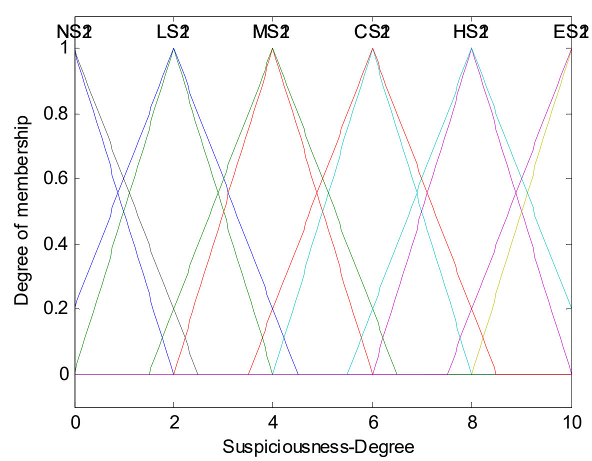

Figure 10: HF Membership function of SD

The moving agents corresponding distances from the assets (AdS) is classified as far (F), close (C), very close (VC), and enormously close (EC) (Figure 11).

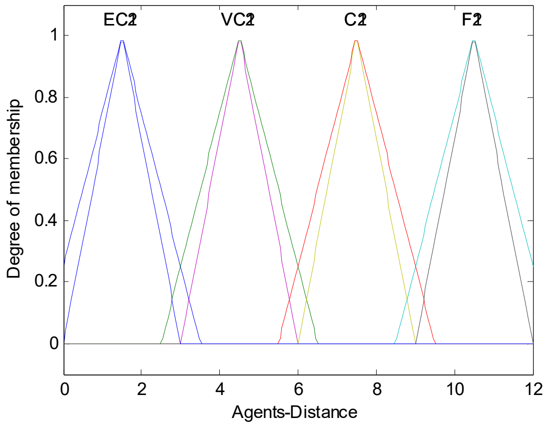

Figure 11: HF Membership function of AdS

The number of moving agents (MaN) is assumed to be variable; for that, they will be characterized as Rare (Ra), Average (Av), Moderate High (MH), and High (Hi) (Figure 12).

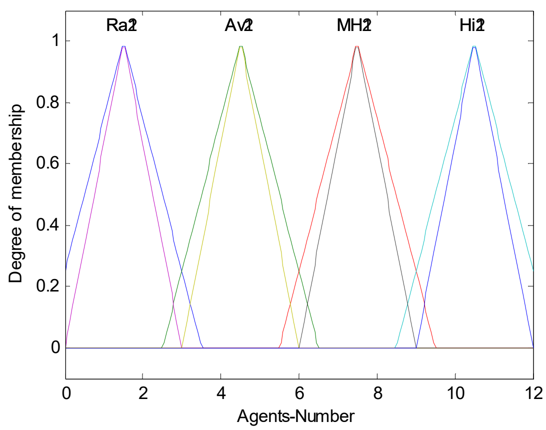

Figure 12: HF Membership function of MaN

The third input which is the value of the assets (AsV) has four main classes which are Not Expensive (NE), Average Expensive (AE), Expensive (E), and Too Expensive (TE) (Figure 13).

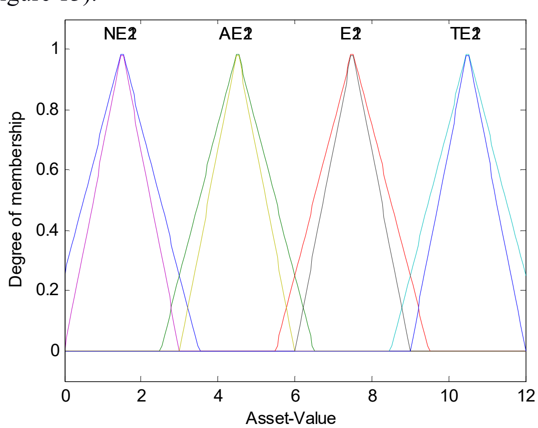

Figure 13: HF Membership function of AvS

The following figures shows the FIS of HF that controls and fine tune FEKF (Figure 14) and then the FIS surfaces of AdS vs MaN and AvS vs MaN respectively (Figure 15 and Figure 16).

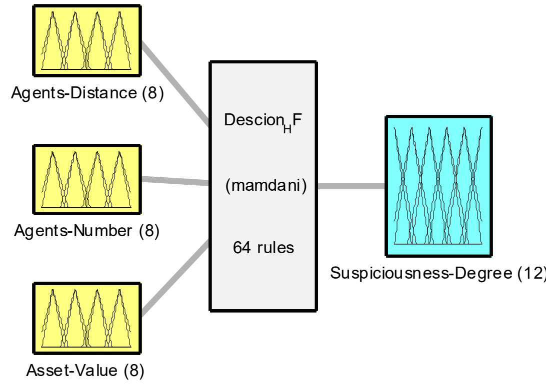

Figure 14: Decision Making HF logic decide the SD of each agent

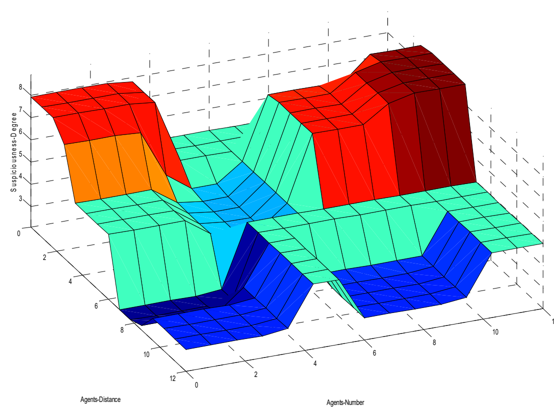

Figure 15:FIS Surface of SD with agents' number and distances as two inputs

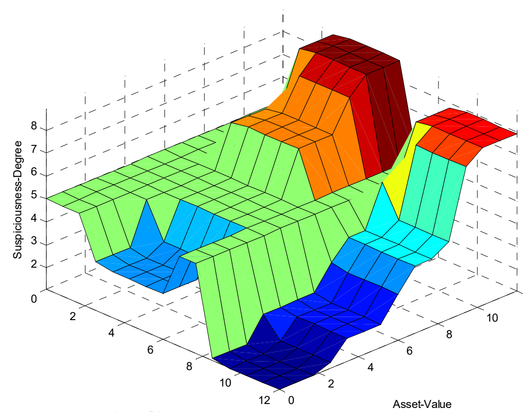

Figure 16: FIS Surface of SD with agents' distances and assets value as two inputs

11. Monitoring System Animation

Animating the monitoring environment including the moving agents and the sensors that track their movements in real-time is an effective addition that shows how every single component work together to emphasize the

functionality of the system elements, the sensors in action, and how the decision is made based on the collected data. Matlab based code and plots were created to simulate the proposed monitoring environment system. Sonars, IRs and Pressure sensor floor were designed carefully to track any moving object and how far or close are they from the monitored valuable assists. Three Sonar and IR arrays follow each agent while he/she is in covered area. The floor shows how the tiles interact with all agents showing their perspective locations and weights. Once the agent is detected initially with the pressure floor, the other sensors start to follow and feed the distance of the moving agent from the assets and his/her speed.

Figure 17 shows how the monitoring system is implemented and the location of all the sensors.

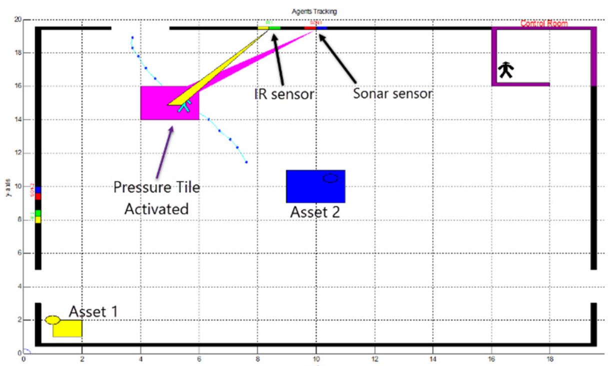

Figure 17: Animation of the monitoring system, sensors, assets and moving agents "Matlab"

12. Discussion and Future Work

FEKF provided a new extension of the EKF that allow to reduce the uncertainty in both the process and measurements under the FL supervision. Tuning the measurement noise covariance values R and process noise covariance Q showed how combining both FL and EKF can result in more stable estimations and reliable decisions consequently, FEKF namely.

Sensors similarity was performed utilizing MF to combine the homogeneous sensory data into a single data as well as their corresponding error covariances. Figure 18 provided below illustrate how the MF sensors within their groups can perform better.

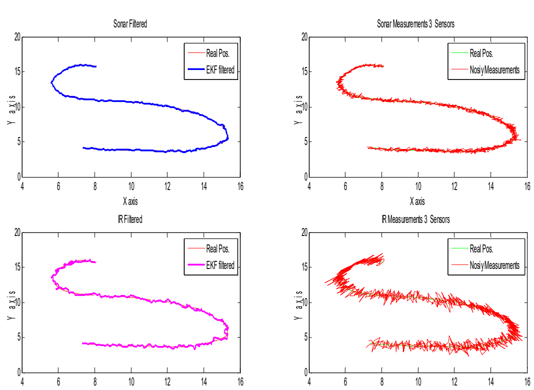

Figure 18: MF sonar and IR sensors

SVF was then applied to combine the resultant of measurement fusion inside the loop of iteration of FEKF which proved how the fused data can be more reliable and accurate if compared to the ordinary estimation method (Figure 19).

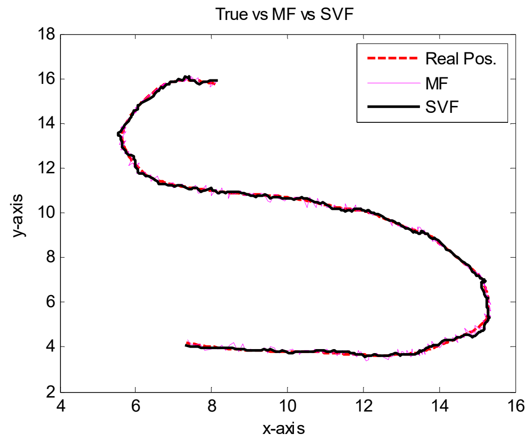

Figure 19: SVF compared to MF

The figure (Figure 20) below also shows how FEKF methodology can enhance the ordinary EKF where the mean square errors for both axis are compared.

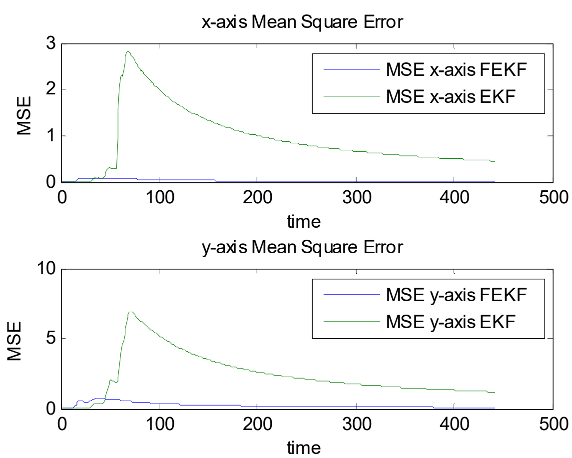

Figure 20: Mean Square Error FEKF vs EKF

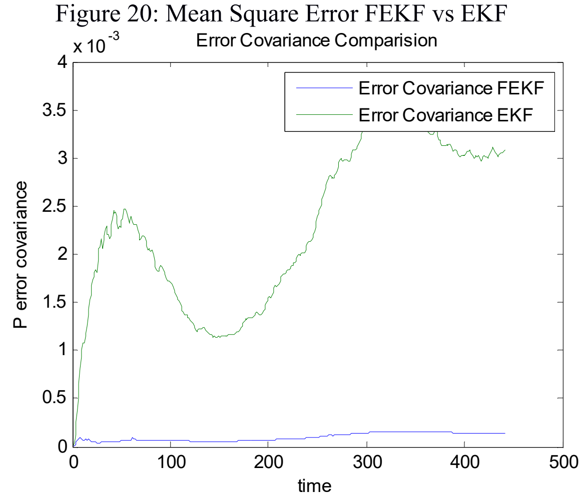

Figure 21: Mean Square Error FEKF vs EKF

Once the positons and weights are estimated for each agent, the data is sent to Hyper-Fuzzy Logic HFL to process their status and the degree of suspiciousness accordingly.
This monitoring system provides an advance security system that exceed many other systems utilizing unexpansive and affordable sensors sets.
The Matlab code for estimation and animation execution time was about 4.05 seconds for one agent moving more than 15 meters; however, with more sensors and agents' simulation the execution time of the code have increased slightly with an acceptable variance that allow the system to track agents and make decisions in real-time applications.

13. Conclusions

In this paper, a new security monitoring system applying data sensor fusion with the aid of Fuzzified extended Kalman filter have been developed and simulated. Sensors similarity and complementarity were the preprocessing methods for all sensors data which helped to feed the EKF with more accurate measurements and prevent the other uncertain readings from interfering during the filtering process. Fuzzified EKF sensor fusion has proven that multi-sensor security systems can outperform the systems which are based on single sensor measurements.

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